Fault Diagnosis System for Turbo-Generator Set Based on Fuzzy Neural Network

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Abstract

When a fault such as unbalance occurs in a turbo-generator set, sensors should be put on its bearing to detect vibration signals for extracting fault symptoms, but the relationships between faults and fault symptoms are too complex to get enough accuracy for industry application. In this paper, a new diagnosis method based on fuzzy neural network is proposed and a fuzzy neural network system is structured by associating the fuzzy set theory with neural network technology. Especially, an effective fuzzy organization method for training samples is presented, fault symptoms are discretized by a focusing quantization method and are then fuzzified to obtain fuzzy sets. In addition, the standard fault data which is confirmed by application is added to the standard fault case database in order to improve accuracy of diagnosis system. Finally, a vibration fault diagnosis system for 600MW turbo-generator set is designed and realized by the proposed fuzzy neural network system structure, its running results show that the new diagnosis system can satisfy fault diagnosis requirement of large turbo-generator set, its accuracy varies from 92 percent to 98 percent.

Keyword: Fault diagnosis, fault symptom, fuzzy neural network, focusing quantization

I. Introduction

Along with the development of modern science and technology, turbo-generator sets in thermal power plants are becoming larger and more complex in order to raise efficiency. Wide applications of large-scale turbo-generator sets in thermal power plants bring huge economic benefit, but also cause a series of problems [1]. Investment and maintenance of these equipments are unbearable and accidents caused by them are serious. Therefore, it is very important for thermal power plants to diagnose and eliminate faults of large-scale turbo-generator set.

In order to diagnose and eliminate faults of large-scale turbo-generator set, the following three points must be studied deeply. First is the study of failure mechanism, second is the choice of fault symptoms and its threshold, third is the processing method of fault data. Thereinto, failure mechanism is physical base of fault diagnosis, choice of fault symptoms and its threshold should also be confirmed according to failure mechanism and practical experience. Large-scale turbo-generator set is a kind of complex system both in structure and in function, which contains the process of converting heat energy to mechanical energy and the process of converting mechanical energy to electric energy, including thousands of parts and components related to operation, maintenance and control. Every part of large-scale turbo-generator set is designed and operated in a certain critical condition and interacts between each other. It will lead to failure of the whole system if any part doesn't work. The occurrence and transmission of failure and its symptoms in components are very complicated. Failure mechanism and its propagation mechanism are not very clear yet. Therefore, substantial progress can only be achieved by long-term hard working of researchers. Thereupon, there are two difficulties in fault diagnosis of large-scale turbo-generator set: one is it is very difficult or even impossible to model a large-scale turbo-generator set for fault diagnosis. The other is the relationships between faults and fault symptoms are so complex, diagnostic process itself contains fuzziness. Based on current research of failure mechanism, one of the main measures to improve accuracy of diagnosis system is to develop an effective fault data processing method and establish an intelligent fault diagnosis system for large-scale turbo-generator set.

Nowadays, many intelligent methods such as fuzzy diagnosis system and neural network diagnosis system as well as expert diagnosis system are applied to large-scale turbo-generator set [2-4]. As to expert diagnosis system, there are still many problems such as automated knowledge acquisition, establishment and maintenance of knowledge database, organization and reasoning of diagnosis knowledge. A great breakthrough should be made by scientists and domain experts to work hard together before it is applied to practice. Correspondingly, fuzzy diagnosis system and neural network system can be realized more easily. However, their diagnostic accuracy can not satisfy industry application. Therefore, fuzzy set theory is associated with neural network technology and then a fuzzy neural network system is proposed for complex system's fault diagnosis in this paper. Especially, an effective fuzzy organization method for training samples of neural network is presented, fault symptoms are discretized by a focusing quantization method and are then fuzzified to given fuzzy sets, the training sample database for diagnosis neural network is then established. In addition, standard fault data which is confirmed by practical application is added to the standard fault case database of diagnosis neural network in order to improve accuracy.

Finally, supported by the 108DAI detecting system, vibration signal in radial and axial direction can be got by its sensors, showed in figure 1. Then, a vibration fault diagnosis system for 600MW turbo-generator set is designed and realized by the proposed fuzzy neural network system structure, its running results in a thermal power plant of Guangdong Province show that this new diagnosis system can satisfy fault diagnosis requirement of large-scale turbo-generator set.

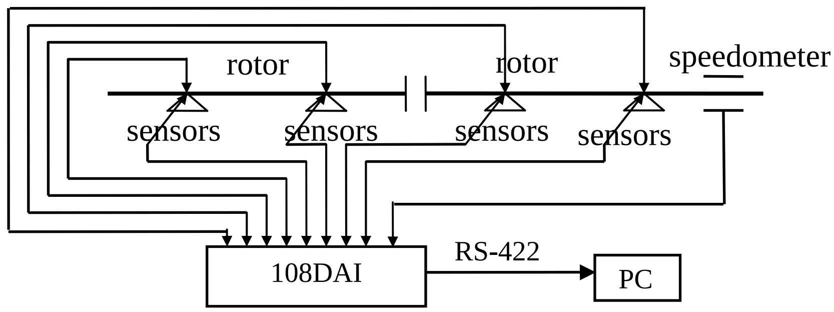


Fig. 1. The structure of diagnosis system supported by the 108DAI detecting system

II. Structure of Fuzzy Neural Network Diagnosis System

Fault diagnosis is a kind of pattern classification. Generally, failure signal is analyzed to extract fault symptoms, and then a recognition rule such as euclid criterion is used to identify faults. However, only partial information in different fault state can be considered in a certain recognition rule when a diagnosis decision is done. So identification can't be carried out if some faults aren't considered in advance. As far as a complex system such as a large-scale turbo-generator set is concerned, it is so difficult to choose suitable identification rules to diagnose faults.

As a kind of adaptive pattern recognition technology, artificial neural network (ANN) is suitable for establishing intelligent fault diagnosis systems of complex system. Firstly, characteristic of ANN is determined by network topology, characteristic of nodes and learning algorithm. It can fully utilize the information in different fault state and then train an ANN to achieve balanced connecting weights, which represent mapping relationships between ANN and fault patterns. Secondly, ANN can learn from fault data continuously, its connecting weights can be adapted according to the change of running environment, so it can approach expected object more accurately. Owing to the uncertain failure mechanism, ANN is applied more and more to fault diagnosis of complex systems recently. People expect that trained ANN has the ability to classify faults by learning diagnosis knowledge from fault data and then it is not necessary to pay attention to failure mechanism inside a complex system any more. However, if an ANN is directly regarded as a diagnosis system, this system is in short of adaptive and self-learned ability because there is no appropriate function module connecting to learning-revise section and input-output section. This disadvantage becomes much obvious to complex systems. Therefore, diagnosis system's structure consisting of ANN should be designed in detail according to diagnosis problem.

On the other hand, complexity of failure mechanism and coupling effect between fault symptoms lead to fuzziness and uncertainty of fault diagnosis process. Though ANN has strong ability of self-learning, association and identification, it can handle complexity but not fuzziness. Fuzzy set theory can handle fuzziness effectively but has no self-learning ability. Associating fuzzy set theory with ANN technology, it is undoubtedly effective to utilize a fuzzy neural network to fault diagnosis of complex system. Fuzzy neural network has been applied to vibration fault diagnosis of rotating mechanism recently, the results indicate that it is much more effective than normal ANN or fuzzy system if the fault data is complex and contains fuzziness.

In the field of fault diagnosis, there are two methods to structure a fuzzy neural network. One is to structure a corresponding neural network system directly according to fuzzy rules or fuzzy algorithm, the other is to structure a composite diagnosis system by associating fuzzy classifying method and neural network model.

Fuzzy neural network structured with the first method is transformed from corresponding fuzzy system which has the same function, it is not a black box any more. All its nodes and connected weights have their special physical significance, which are corresponding to membership functions and factor weights of fault symptoms to fault patterns in the corresponding fuzzy system. Generally, a mellow fuzzy diagnosis system can be transformed to a fuzzy neural network diagnosis system to improve diagnostic accuracy by means of the adaptive and self-learning ability of ANN. However, it is very difficult to obtain mature diagnosis rules for a complex system.

There are two methods to get a composite diagnosis system. One is to apply fuzzy concept to input and output layer of neural network, i.e. a fuzzy layer is added before input layer and a fuzzy decision layer is added after output layer of a conventional ANN. That is to say, ANN is directly regarded as a diagnosis model. The other method is to associate fuzzy classifying method with neural network according to the special diagnosis problem, and then different function is realized by fuzzy system or neural network suitably. The second method can structure a general fuzzy neural network diagnosis system and obtain a high accuracy by choosing a proper associate scheme according to practical application, so it is adopted in this paper.

In order to get an appropriate composite diagnosis system, the principle of fault diagnosis should be obeyed. According to fault diagnosis principle, fault signal should be analyzed and compared with standard samples so as to judge if a system is normal. If a system is abnormal, fault symptoms will be extracted from fault signal by a given algorithm and then diagnosis decision will be made. Fault diagnosis for complex system often requires such a repeating searching process: detection, then diagnosis, and then detection and diagnosis again. According to this principle, a fuzzy neural network diagnosis system is presented in this paper. System structure, which contains two forward paths and one outer loop, is shown in figure 1. The first path completes task of training diagnosis neural network, which includes four modules: fault case organization, fault symptom extraction, fuzzy organization and ANN model. The second path completes task of diagnosing faults, it also includes four modules: data organization, fault symptom extraction, fault data fuzzification and trained ANN. The outer loop is used to verify diagnosis results and add the standard fault data which is confirmed by practice to standard fault case database.

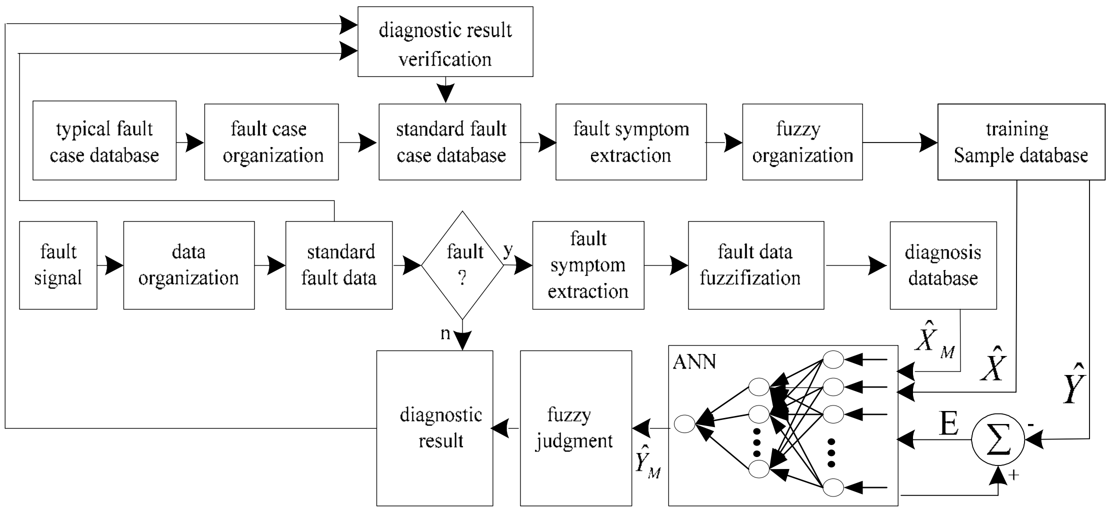


Fig. 2. The structure of fuzzy neural network diagnosis system

Working principle of this system is as follows, first, fault data in typical fault case database is organized to get a standard format, fault data in standard format and standard samples are placed in standard fault case database, second, fault symptoms are extracted from fault data by using some signal analysis method and data processing algorithm, third, training samples are organized according to some rules, fourth, ANN is trained by these organized training samples. Diagnosis rules are hidden in connecting weights of trained ANN. Then, the second path completes fault diagnosis. First, fault signal is organized to get a standard format and is compared with standard samples in standard fault case database to judge if the system is normal. If the system is abnormal, fault symptoms are extracted from fault data, and are then fuzzified to given fuzzy sets and organized to be input data in diagnosis database. Second, input data is input to trained ANN, trained ANN will output membership function value to different faults. In the end, diagnostic result will be obtained by fuzzy judgment.

Obviously, ANN in this system only completes the task of fault classification. In order to train ANN correctly, it is necessary to organize typical fault cases to get a standard format, this task is completed by fault case organization module. But it is improper to train ANN directly by fault data in standard format, fault symptoms should be extracted from fault data and this task is finished by fault symptom extraction module. Fuzzy organization module organizes training samples according to a certain principle. That is to say, training samples are calculated and organized by fault case organization module, fault symptom extraction module and fuzzy organization module, so ANN has a good benchmark for self-learning. This is very important for improving the accuracy of ANN diagnosis system. In order to improve the accuracy, confirmed fault data is added to standard fault case database by diagnostic result verification module. That is to say, unconsidered fault mode will be added to standard fault case database to avoid misdiagnosis and missing diagnosis, diagnostic ability of this system can be improved along with the running of the system.

When the system is designed, its diagnostic ability is mainly determined by the validity and perfectibility of training sample database, the organization of training samples and training degree of ANN, i.e. its diagnostic accuracy is determined by four modules: fault case organization module, fault symptom extraction module, fuzzy organization module and ANN model. Therefore, these four modules should be well designed according to present knowledge of failure mechanism. Based on the research production, format of standard fault case database is formalized, then fault symptom extraction method and three-layer forward ANN model shown in paper [1] are adopted in this paper. Primary work of this paper is to propose a fuzzy neural network diagnosis system structure shown in figure 1, and then design an effective fuzzy organization method for training samples and input data of diagnosis neural network to improve diagnostic accuracy of the diagnosis system.

III. Fuzzy Organization for Training Samples and Input Data

Organization of training samples and input data is an important part of ANN diagnosis system, but it was neglected before and fault cases were classified by domain experts to get training samples. It is acceptable to organize simple fault cases based on experts' experience. As for complex systems, fault symptoms are very complicated and interact each other. There will be misdiagnosis or missing diagnosis if training samples and input data are not organized well. Therefore, an effective fuzzy organization method for training samples and input data is presented in this section.

In order to obtain training samples, fault signal should be organized to get fault data in standard format, then fault symptoms are extracted from fault data by using a signal analyzing method and data processing algorithm, finally membership function of every fault symptom to every fault is calculated to get training samples.

For extracting fault symptoms, FFT method was popularly adopted to calculate the amplitude and phase of each harmonic component in vibration fault signal, 7 symptoms extracted from 3 frequency components were then regarded as fault symptoms. According to the research of failure mechanism of 600MW turbo-generator set, FFT method and graphics analyzing method are adopted to extract fault symptoms from 5 frequency components of vibrating signal, 18 fault symptoms are obtained and their thresholds are chosen according to domain experts' experience in this paper. There are 4 fault symptoms in axis direction and 14 in diameter direction: 1) total amplitude of vibration signal in axial direction, 2) total amplitude of vibration signal in radial direction, 3) fundamental component amplitude of vibration signal in axial direction, 4) fundamental component amplitude of vibration signal in radial direction, 5) second multiple frequency amplitude of vibration signal in axial direction, 6) fundamental component phase difference of vibration signal in axial direction, 7) fundamental component phase difference of vibration signal in radial direction, 8) the change rate of fundamental component phase difference of vibration signal in axial direction, 9) the change rate of fundamental component amplitude of vibration signal in radial direction, 10) amplitude from 0.35 to 0.50 multiple frequency of vibration signal in radial direction, 11) all components of vibration signal in radial direction, 12) The climbing-speed of total amplitude of vibration signal in radial direction, 13) the change rate of phase difference of vibration signal in radial direction, 14) the proportion of fundamental component amplitude in total amplitude of vibration signal in radial direction, 15) dynamic stiffness of bearings, 16) total amplitude of vibration signal in radial direction at the critical speed, 17) the proportion of second multiple frequency amplitude in total amplitude of vibration signal in diameter direction, 18) the proportion of the fundamental and second multiple frequency amplitude in total amplitude of vibration signal in diameter direction.

These 18 fault symptoms can get further information from fault data than the 7 symptoms extracted only by FFT method. These 18 symptoms should be fuzzified to obtain fuzzy sets. A focusing quantization method is adopted to calculate the membership function value of each fault symptom to each fault pattern. The focusing quantization algorithm includes three steps, which are shown as follows,

Step1, initial curve of extended membership function should be obtained according to the experience of domain experts [5].

Step2, a focusing factor F should be chosen according to the actual situation of fault symptom, where $F \in (0,1)$, then focusing quantization of a fault symptom can be done by using F. Steps of implementation of focusing quantization are as follows,

1) To define domain area of each fault symptom and its quantization number, not losing the generality, let quantization number is 2n+1.

2) To make sure the fault symptom type. The first type is high-limited symptom whose value is the smaller, the better, the second type is low-limited symptom whose value is the bigger, the better, the third type is bi-limited symptom whose value is appreciated to be mezzo.

3) For the first type of fault symptom, its intersection point M between normal value and abnormal value is regarded as its focus, its lowest value 0 will be regarded as its staring point, its maximal value is A, then it is quantized to 2n+1 parts in value domain [0, A]. The division point is as follows,

$$
\begin{aligned}
&M \times F \\
&M \times F + M \times F^2 \\
&\ldots\ldots \\
&M \times F + M \times F^2 + M \times F^3 + \cdots + M \times F^n \\
&N \times F - N \times F^2 - N \times F^3 - \cdots - N \times F^n + M \\
&\ldots\ldots \\
&N \times F - N \times F^2 + M \\
&N \times F + M
\end{aligned}
$$

Where N = A − M, then this symptom is quantized to 2n+1 parts: {0,1,2,…,2n}.

4) For the second type of fault symptom, its intersection point M is regarded as its focus, its maximal value B is regarded as its staring point, its lowest value is 0, then it is quantized to 2n+1 parts in value domain [0, B]. The division point is as follows:

$$N \times F + M$$
$$N \times F - N \times F^2 + M$$
$$\cdots\cdots$$
$$N \times F - N \times F^2 - N \times F^3 - \cdots - N \times F^n + M$$
$$M \times F + M \times F^2 + M \times F^3 + \cdots + M \times F^n$$
$$\cdots\cdots$$
$$M \times F + M \times F^2$$
$$M \times F$$

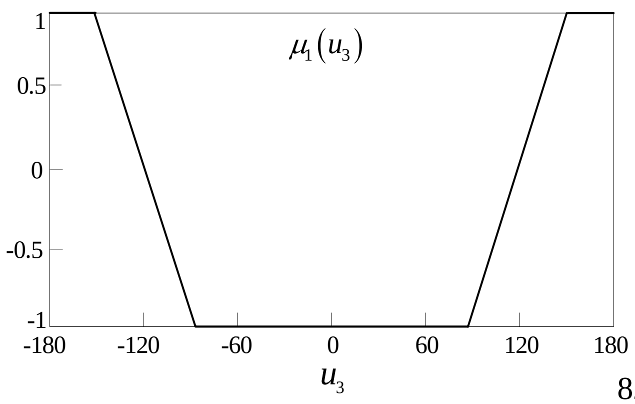
Where N = B − M, then this symptom is quantized to 2n+1 parts: {0,1,2,…,2n}.

5) For the third type of fault symptom, its intersection point between normal value and abnormal value is also regarded as its focus. Here, there are two focus M1 and M2 because its normal value is in the middle parts of value domain [0, D], let the best value of this fault symptom is C. Turbo-generator set is abnormal if this symptom's value is bigger than upper limit or less than lower limit, so C is regarded as a division point and then get two parts to be quantized respectively. If its value is in [0, C], it can be quantized by the same method as the second type and then is quantized to 2n+1 parts {0,1,2,…,2n}. If its value is in [C, D], it can be quantized by the same method as the first type and then is quantized to 2n+1 parts {0,1,2,…,2n}.

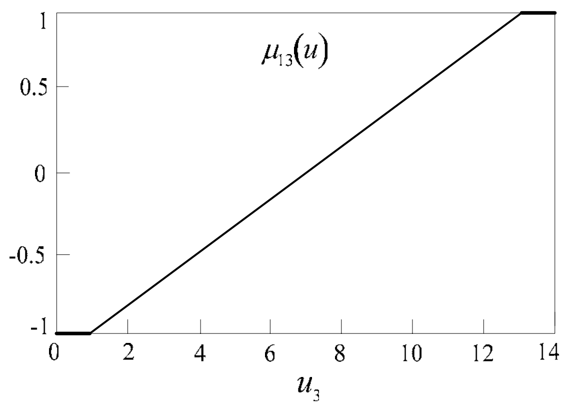
After all fault symptoms have been quantized by focusing quantization algorithm, they are converted to be unilateral value and 0 represents the best value of each fault symptom, that is to say, all input is standardization. It is convenient to apply fuzzy neural network system to diagnose faults for turbo-generator sets.
In the end, based on the curve of initial extended membership function, we can redefine the curve of new membership function according to the quantization result of all fault symptoms. There is a principle that all points whose membership function value is 1 will be invariable.

For example, the curve of initial extended membership function of fundamental component phase difference of vibration signal in radial direction (fault symptom u_3) to the fault of rotor_bend (v_1) is shown in (a) of figure 3. According to the practical condition of u_3, a focusing factor F_{13} = 0.5 is selected. Value domain of u_3 is [-180, 180], quantization number is 2n + 1 = 15, M = 120. After quantizing u_3 by F_{13}, the curve of new membership function is shown in (b) of figure 3.

In figure 3, the point of u_3 = 1 in (b) corresponds to the point of u_3 = 90 in (a), the point u_3 = 13 in (b) corresponds to the point u_3 = 150 in (a), transition area from 1 to 13 in (b) is more particular than that in (a). The focusing quantization algorithm has improved the resolution near the focus so that the diagnostic accuracy of fuzzy neural network diagnosis system can be improved obviously [6].



(a)



(b)

Fig. 3. The curve of membership function of u_3 to v_1

After quantization, membership functions of 18 fault symptoms to 6 typical fault patterns (such as rotor_bend, blade's drop-off, oil-whip, rub-impact, unbalance and misalignment) in 600 MW turbo-generator set can be obtained. The membership function value of fault symptoms to every fault pattern will be regarded as input sample and the membership function value of typical fault cases to every fault pattern will be regarded as output sample, then training samples can be obtained.
Input data can be organized according to the same principle.

™ . Experimental Results

Supported by the 108DAI detection system, a diagnosis system for typical vibration faults of 600MW turbo-generator set is designed based on the fuzzy neural network diagnosis system structure. In this system, a three-layer neural network with an error backpropagation training algorithm is adopted in this diagnosis study. There are 18 input nodes which correspond to membership functions of 18 fault symptoms respectively, and the number of output nodes is fixed at 7, the first output node presents 1 if the turbo-generator set is normal, the next 6 output nodes present the membership function value of input fault data to six typical fault patterns respectively. The number of processing elements in the hidden layer, learning constant, momentum term, number of learning times, and upper bound of error value are all programmable. The neural network's transfer function is the hyperbolic tangent sigmoid function as follows,

$$f(x)=2/(1+\exp(-2x))-1 \quad \textbf{(1)}$$

When a new fault pattern occurs in input fault data, that is to say that this fault case does not belong to the 6 typical fault patterns or normal state, the first output node of the fuzzy neural network will output 0, the 7th fault pattern appears. After confirmation by practical application, the standard fault data which presents the 7th fault pattern will be added to the standard fault case database to improve the diagnostic ability of the whole system. The working principle of this system is shown in figure 4.

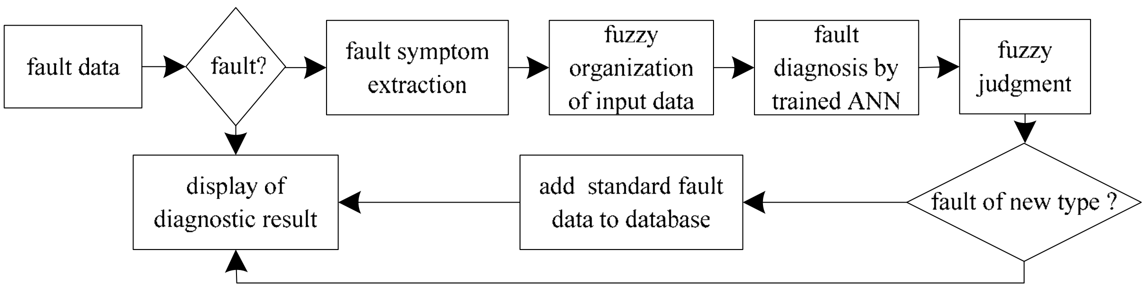


Fig. 4. The working principle of fuzzy neural network diagnosis system

200 cases of typical vibration faults of 600MW turbo-generator sets in a thermal power plant of Guangdong Province were collected in 4 years. Fault data was collected from 2 turbo-generator sets belonging to the same type. Two probes were set on each bearing of turbo-generator set to detect vibrating signal of horizontal and vertical direction when these 200 cases were collected.

After fuzzy organization, 100 cases were regarded as the training set and the other 100 cases were regarded as the testing set. According to the working principle in section 2, ANN is trained by the first path in figure 1, and then the second path in figure 1 will complete fault diagnosis according to the principle in figure 4.

The trained fuzzy neural network diagnosis system was verified by the testing set, its accuracy is shown in table 1. In order to compare this system with others, a three-layer BP neural network diagnosis system which has the same network structure with the fuzzy neural network diagnosis system in figure 1 is designed, but it has no fuzzy organization module. Other system such as ANN is directly regarded as a diagnosis system is not discussed here, because its accuracy is too low.

Table 1. The diagnostic results of two diagnosis systems

Fault class	Accuracy of three-layer BP neural network diagnosis system	Accuracy of fuzzy neural network diagnosis system
rotor_bend	83%	96%
blade's drop-off	83%	94%
oil-whip	79%	92%
rub-impact	89%	95%
Unbalance	88%	98%
misalignment	87%	97%

The diagnostic results indicate that the fuzzy neural network diagnosis system has much higher accuracy than BP neural network. This is because the focusing quantization algorithm has improved the resolution in the transition area of fault symptoms from normal value to abnormal value.

The diagnosis system has been run for more than one year in a thermal power plant of Guangdong Province. Its running results show that the rate of misdiagnosis and missing diagnosis for the six typical fault patterns is lower. Some thoughtless fault patterns can be identified by this diagnosis system after enough fault data which presents new fault patterns is added to the standard fault case database.

∏. Conclusion

Based on the research production of failure mechanism of large-scale turbo-generator set, a new structure of fuzzy neural network diagnosis system is proposed by associating fuzzy set theory with neural network technology. 18 fault symptoms are extracted from standard fault data and their thresholds are chosen according to domain experts' experience. A focusing quantization algorithm is adopted to organize training samples for diagnosis neural network. In addition, the standard fault data which is confirmed by practical application is added to the standard fault case database in order to improve the accuracy of diagnosis system. In the end, supported by the 108DAI detecting system, a vibration fault diagnosis system for 600MW turbo-generator set is designed and realized by the proposed fuzzy neural network system structure. The system has been run for more than one year in a thermal power plant of Guangdong Province. Its running results show that the rate of misdiagnosis and missing diagnosis to the six typical fault patterns is lower. Some thoughtless fault patterns can be identified by the diagnosis system after enough fault data which presents new fault patterns is added to the standard fault case database. It is expected that this system can be applied to vibration fault diagnosis for large-scale turbo-generator set.

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